# To Share or Not to Share? Knowledge Convergence and Divergence in Cross-Disciplinary Collaboration

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*For cross-disciplinary teams to be effective, what knowledge should be shared and what knowledge should remain unique to individual team members? We adopted a mixed-method approach using a sample of grant-funded teams composed of principal and co-principal investigators of diverse disciplines. Interviewees and survey respondents especially favored knowledge similarity over uniqueness for team vision and teamwork, but less preference for convergence emerged for research outcomes and research content (theory, operational details of methodology, analysis). Moreover, more team knowledge convergence was associated with higher perceived collaboration satisfaction and trended in the direction of more grants, publications, and conference presentations.*

*Keywords: team cognition, knowledge convergence, knowledge divergence, cross-disciplinary teams, interdisciplinary teams, team mental models*

## INTRODUCTION

How can teams best harness individual expertise so that relevant information is shared with whom and when it is most needed to build effective collaboration? This question is especially salient in cross-disciplinary teams, which are engineered for knowledge diversity by inviting members from diverse disciplines to integrate knowledge and derive innovative outcomes (e.g., Bammer et al., 2020). “Grand challenges” that represent exceedingly complex problems, such as sustainability, poverty, and cybersecurity cannot be solved by single individuals or specializations and therefore demand broad representation across multiple disciplines (De Grandis & Efstathiou, 2016). However, cross-disciplinary teams must also build substantial integration to make the best use of diverse expertise (Allen et al., 2017; Bammer et al., 2020; O’Rourke et al., 2016).

Leveraging member expertise requires that some information remain individually held and some information be shared among team members (e.g., Lewis & Herndon, 2011; Mohammed et al., 2021). On the one hand, the diversity of expertise is the central reason why cross-disciplinary teams are formed (e.g., Cronin & Weingart, 2007). On the other hand, unattended differences in members’ knowledge can be counterproductive (e.g., Brugnach and Ingram 2012; Cronin & Weingart, 2007; Lewicki et al., 2003). Some level of shared understanding must exist before groups can operate as a unified structure with similar purposes and priorities (e.g., Klimoski & Mohammed, 1994). Therefore, both a “divergence and convergence of meanings” must be achieved (Fiol, 1994, p. 404). Yet, arriving at a shared understanding may undermine diversity and vice versa, as knowledge divergence and convergence are opposing forces (Mohammed et al., 2021).

What knowledge should be shared and what knowledge should remain unique to individual members for cross-disciplinary teams to be effective? When is knowledge convergence optimal and when is divergence optimal? Addressing these questions is crucial because building shared knowledge in teams requires high coordination and communication costs, which can tax members’ limited attentional and temporal resources (e.g., Grand et al., 2016). This is especially the case in cross-disciplinary teams when “greater differentiation in member specialization requires individuals to rely more on decoding and communication processes to acquire knowledge, thus creating greater potential for inefficiencies during team knowledge-building” (Grand et al., 2016, p. 1366). Therefore, converging when diverging is needed mishandles team resources. Contrastingly, diverging when converging is needed may impair team processes and performance (Crawford & LePine, 2013).

Regrettably, however, the team cognition and cross-disciplinary team literatures provide few answers and little guidance regarding the complex process of knowledge sharing in cross-disciplinary collaborations (Fazey et al., 2014) or how knowledge convergence and divergence should be balanced (Mohammed et al., 2021). Seeking to address these deficiencies, the objective of this research was to explore the effects of simultaneously held knowledge divergence and convergence in cross-disciplinary research teams. Our research questions include: 1) What knowledge should be shared versus uniquely held by cross-disciplinary team members? 2) How does the extent to which cross-disciplinary team members report more of a unique or shared understanding of relevant team knowledge influence a) affective (perceived collaboration) and b) performance (archivally measured productivity) outcomes?

In answering these research questions, we contribute to the team cognition literature (e.g., Mohammed & Dumville, 2001; Mohammed et al., 2021), which has emphasized the need for members to “get on the same page,” but has not addressed what areas of expertise should remain unique. Specifically, we address largely unanswered calls in team cognition research to move beyond naive assumptions (e.g., more sharing is always better) toward increased conceptual sophistication (e.g., balancing knowledge convergence and divergence; Mohammed et al., 2010). By exploring both ends of the knowledge divergence-convergence continuum, we also foster the frequently requested but uncommon cross-fertilization across team cognition sub-literatures, which have focused on either divergence (e.g., transactive memory systems) or convergence (team mental models) (e.g., DeChurch & Mesmer-Magnus, 2010).

By merging what knowledge should remain uniquely held and what should be shared, we also contribute to the cross-disciplinary team literature, which has also mainly emphasized managing the integration-related challenges of bringing diverse disciplines together (Ávila-Robinson & Sengoku, 2017; Defila & Di Giulio, 2015; Salazar et al., 2012). Despite the “implicit assumption that all integration is good,” however, “it is unclear how much integration is required to maximize benefits to participating fields. Mere exposure to new disciplines may suffice” (Balakrishnan et al., 2011, p. 530). By better mirroring the practical realities of teams, our results also offer preliminary guidance to cross-disciplinary researchers regarding what knowledge should be prioritized for sharing.

To accomplish our research objectives, we adopted a sequential mixed-method approach (Molina-Azorin et al., 2017), using inductive and deductive methodologies. We first conducted 33 semi-structured interviews with grant-funded PIs and co-PIs, who reflected on what knowledge should be shared and what should be unique among cross-disciplinary team members. Based on the qualitative results derived from coding the interviews, we designed and administered a quantitative survey measuring the extent of knowledge convergence, completed by 38 grant-funded PIs and co-PIs. We then examined the relationship between survey data and archival measures of research productivity (number of PI/co-PI grants, publications, and conference presentations). We conclude by highlighting theoretical and practical implications for cross-disciplinary team members, as well as future research directions.

## Theoretical Background

From the inception of the team cognition literature, the notion of sharedness has incorporated two distinct interpretations; convergent/overlapping/having in common (e.g., shared equipment) and divergent/distributed/dividing up (e.g., shared workload) (Cannon-Bowers, Salas, & Converse, 1993; Klimoski & Mohammed, 1994; Resnick, 1991). Convergent knowledge refers to "meanings and understandings that are alike among individuals and utilized to make sense of, attribute meaning to, and interpret internal and external events" (Rentsch et al., 2008, p. 144). In the context of cross-disciplinary teams, knowledge convergence describes the integration of theories, methods, and approaches from traditionally diverse scientific and technological disciplines such as chemistry, psychology, computer science, communication, and mathematics (Sharp *et al*., 2016).

In contrast, divergent knowledge takes a complementary form in which "individuals' cognitions must fit together to compensate for gaps in others' understandings of a knowledge domain" (Rentsch et al., 2009, p. 246). For the purpose of this paper, we define knowledge divergence as diversity in domains of knowledge expertise (Paletz & Schunn, 2009). We focus on the contributory expertise (knowing-that and knowing-how) of team members needed to add value to a field (Bammer et al., 2020).

Some forms of team cognition (e.g., team mental models) emphasize the convergent definition of sharing, assuming higher performance will result when team members hold more similar conceptualizations of relevant team knowledge (Mohammed et al., 2010). In contrast, other forms of team cognition, such as transactive memory systems, have focused on the divergent definition of sharing, which assumes that team outcomes will be enhanced when members possess a broad coverage of unique information (e.g., Lewis & Herndon, 2011). Several meta-analyses confirm that team knowledge convergence and knowledge divergence each positively and uniquely predict performance (e.g., DeChurch & Mesmer-Magnus, 2010; Mesmer-Magnus et al., 2017; Niler et al., 2020). However, because team cognition research streams have adopted an either/or approach, how knowledge convergence and divergence should be balanced has gone unaddressed (Mohammed et al., 2021).

The artificial dichotomy between knowledge divergence and convergence in the team cognition literature promotes the improbable reality that all knowledge domains in the team need to be completely similar or completely distinct. However, it is more likely that some knowledge will need to be held in common and other knowledge divided up within a team (Cannon-Bowers & Salas, 2001; Rentsch & Hall, 1994). This reality is especially true in cross-disciplinary teams which are defined by non-redundant areas of expertise but must also develop knowledge that is held in common by all members. Because of their specialized expertise, "dissemination of unique knowledge among members requires greater coordination on the part of the speaker and receiver to prepare for, communicate, and interpret new information" (Grand et al., 2016, p. 1375). Therefore, when cross-disciplinary teams build shared knowledge on content that should remain diverse, time and effort are squandered. Likewise, failing to converge on knowledge that should be shared can decrease team innovation and performance (e.g., Carton & Cummings, 2012; Cummings & Kiesler, 2007). Therefore, cross-disciplinary teams are an ideal context in which to explore the integration of knowledge divergence and convergence.

Calls to adopt a more sophisticated conceptualization of knowledge sharing have been part of a growing consensus in the team cognition (e.g., Cannon-Bowers & Salas, 2001; Cooke et al., 2000; DeChurch & Mesmer-Magnus, 2010a; Mohammed & Dumville, 2001; Rentsch et al., 2009) and cross-disciplinary (e.g., Balakrishnan et al., 2011; Cummings & Kiesler, 2007; Larson et al., 2023) literatures over the years. In response to these research needs, Mohammed and colleagues (2021) adopted a both/and perspective by featuring a knowledge divergence-convergence continuum as a core dimension in an integrative conceptual framework. Doing so addresses the criticisms of an either/or framing by permitting researchers to answer, “What is the extent of knowledge sharing?” on relevant team content (e.g., goals, technology, team interaction, situational context). Framing divergence and convergence as a continuum instead of a dichotomy also permits more sophisticated research questions to be answered, including how teams manage the inherent tension between converging on some types of cognitive content and diverging on other types of cognitive content (Mohammed et al., 2021). Building upon this conceptual framework, the current research empirically explores the effects of simultaneously held knowledge divergence and convergence in cross-disciplinary research teams.

**Mixed-Method Data Collection**

The data presented are part of a larger research project using a mixed-method approach combining interview, survey, and archival data from cross-disciplinary researchers. Given the paucity of theory on the balance of knowledge divergence and convergence (Mohammed et al., 2021), we began with an inductive methodology as recommended by methodological fit research (Edmondson & McManus, 2007). Interviews from cross-disciplinary researchers provided open-ended inquiry and rich, detailed, and in-depth information, which was then used to inform survey development (Greene et al., 1989).

By complementing inductive and deductive methodologies, we sought to expand our understanding of the integration of knowledge convergence and divergence, check interview patterns from a different methodological angle, and provide additional insight into the meaning of interview results. In doing so, we capitalized on three key benefits of mixed-method approaches: elaboration, triangulation, and interpretation (Gibson, 2017). Given the complexities of understanding what knowledge should be shared versus remain unique, integrating qualitative and quantitative results increased the potential for achieving a richer and deeper understanding of this complex phenomenon by offering added insight into findings discovered for each method and improving rigor through consistent findings (Molina-Azorin et al., 2017). We also utilized archival data to examine the effect of self-reported survey scales on objectively measured research productivity.

The primary research question addressed via interviews was, “What knowledge should be shared versus uniquely held by cross-disciplinary team members?” Survey items were designed to address the extent cross-disciplinary team members report more of a unique or shared understanding of relevant team knowledge and how that affects perceived collaboration. Archival data were collected to answer how the extent to which cross-disciplinary team members report more of a unique or shared understanding of relevant team knowledge influences research productivity.

**Research Sample**

We utilized a purposive sampling approach to identify the cross-disciplinary researchers who were “likely to yield the information that the [research] focus calls for” (Lincoln & Guba, 1985, p. 261). Specifically, we interviewed and surveyed researchers who had been awarded a National Science Foundation’s (NSF) EAGER (EArly-concept Grants for Exploratory Research) grant. We selected this sample for several reasons. First, EAGER grants support “high risk-high payoff” proposals that are “engineered” for knowledge diversity by requiring cross-disciplinary collaboration across NSF’s seven directorates (e.g., biological sciences; computer and information science and engineering; engineering; geosciences; mathematical and physical sciences; social, behavioral and economic sciences; and education and human resources). As such, EAGER teams provided a fitting context to study cross-disciplinary research collaboration as researchers tackle exploratory and potentially transformative ideas.

Second, this sample selection allowed us to draw from publicly available data, as nsf.gov publishes the names of Principal Investigators (PIs) and co-Principal Investigators (co-PIs) who have been awarded funding. With these names, we were able to collect other publicly available information (e.g., emails from university websites, research output such as publications from google scholar) to create an archival database. Therefore, our sample was limited to only EAGER PIs and co-PIs and did not include what may have been a larger research team including postdocs, graduate students, and undergraduate research assistants. Third, the two-year time frame of EAGER awards allowed us to collect post-award research outputs (e.g., conference presentations, and publications) in a more feasible time frame than longer-term grants.

Our sample was drawn from EAGER awardees in the Secure and Trustworthy CyberSpace (SaTC) program between 2013 (the first year of EAGER grants in this program) and 2019. In our sample, 13 EAGERs were awarded in 2013, 12 in 2014, 14 in 2015, 0 in 2016, 7 in 2017, 0 in 2018, and 12 in 2019. Cybersecurity was the focus of the EAGER grant research (e.g., password security, cybercrime, cyberbullying, privacy, security practices).

The overall individual sample included 149 principal and co-principal investigators (PIs and co-PIs) with a median of 17 years since earning their Ph.D. (mean = 19.83 years, range of 2-54 years). Males represented 66% of the sample. Over 50 different disciplines were represented, with the largest percentage from computer science (34%), followed by psychology (6%), communication (4%), and electrical and computer engineering (4%).

The overall team sample was 58 EAGER-funded team projects comprising 76 awards (collaborative proposals have multiple universities who have their own sub-budgets but comprise the same overall project). The mean team size was 2.81 (median = 3.00, SD = .91). PI/co-PI dyads comprised 59% of the sample, followed by 28% three-person PI/co-PI teams, 10% four-person teams, and 3% five-person teams. Sixty-seven percent (67%) of the teams included members from the same university. Almost half were mixed-gender teams (46%), 40% were male-only teams, and 14% were female-only teams. The mean award amount was $219,153.57 (median = $224,675, SD = $75,610.71), with a range of $31,579 to $316,000.

## INTERVIEWS

### Interview Recruitment and Sample

All 149 EAGER PIs and co-PIs in the sample were contacted via email and asked to participate in an interview-based study on cross-disciplinary team collaboration in their PI/co-PI EAGER team. We conducted 33 interviews in 2020, representing a response rate of 22%.

Independent samples t-tests were used to evaluate mean differences between the 33 interviewed and the remainder of the sample (N = 116) on continuous variables available from archival data (team size, number of years since receiving the grant, award amount, number of universities represented in the grant, and number of years with a Ph.D.). Results showed significant mean differences in team size ($t = 4.77$, $p < .001$), such that individuals from smaller teams ($M = 2.33$, $SD = 0.54$) were more likely to participate in the interviews than individuals from larger teams ($M = 2.95$, $SD = 0.95$).

Consistent with the larger sample, 76% of interviewees were male, 21% were female, and 3% were unreported. The average number of years since interviewees received their Ph.D. (from 2022) was 20.87 (Median = 17, SD = 11.23), with a range of 5 to 53. Interviewees represented 19 universities, and two respondents were from private industry.

The interview sample included 26 distinct EAGER projects (45% of the larger sample of 58 EAGER grants). Seven interviewees (21%) overlapped with other interviewees in representing the same EAGER grant. The average number of years since the EAGER grant was awarded was 4.00 years (SD = 2.21), with a range of 1 to 7 years. Awards averaged $225,272 (Median = $227,709, SD = $84,594), ranging between $31,579 to $316,000.

Interviewees represented an average PI/co-PI team size of 2.33 members (SD = 0.54), with a range of 2 to 4. The gender composition of the teams was mostly male-only (48.48%) and mixed (42.42%), with

9.1% of the teams containing only female team members. Two-thirds (67%) of PI/co-PI teams were from the same university.

**Interview Protocol**

As part of a larger project, PIs and co-PIs participated in 30-minute to one-hour interviews conducted via Zoom between February and November 2020. All interviewees consented to record the interview. The full interview protocol covered four broad categories, including cross-disciplinary training and experiences; the history, workload sharing, and ongoing writing and communication practices of PI/co-PIs collaboration; the factors that facilitated and hindered cross-disciplinary collaboration; and knowledge convergence and divergence.

Most interviewees characterized their EAGER project as interdisciplinary (as opposed to unidisciplinary, multidisciplinary, or transdisciplinary). For the purposes of this research, we focused on the following interview question:

> "[Name of interviewee discipline] and [name of interviewee collaborator(s)' disciplines] fields are very different. There are things that need to stay different because you can't be expected to be an expert in another person's field. But because you are working together, there are things that you need to be on the same page about. I am curious as to your thoughts about what should remain more divergent in your collaboration and what should be more convergent in your collaboration."

**Coding Process**

Interviews were transcribed verbatim by an external service and imported into NVivo (Release 1.5.2) software (QSR International, 2021) for data analysis. Using a thematic analysis approach foundational to qualitative analysis, we engaged in the following steps: familiarizing ourselves with the interview data, generating initial codes, searching for patterns in the data, and defining and labeling essential themes grouped hierarchically to establish relationships within and between them (Braun & Clark, 2006). Initial or first-order codes were defined using the language of participants (Charmaz, 2006) and then grouped into higher or second-order codes that helped to explain patterns in the first-order data (Van Maanen, 1979). The generated second-order codes were fine-tuned, divided into subcategories, or merged together until no new categories were necessary (deep saturation; Morse, 2015). Second-order codes were reassessed to ensure that they met the four requirements of qualitative content analysis, namely unidimensionality, mutual exclusiveness, exhaustiveness, and saturation (Schreier, 2012). During this process, we developed a detailed manual in which second-order codes were labeled, defined, and some inclusion and exclusion criteria to build decision rules and norms. Finally, we combined second-order codes into broader themes that "represent some level of patterned response or meaning within the data set" (Braun & Clarke, 2006, p. 82). Themes were semantic in nature in that they did not extend beyond what the interviewees communicated (Braun & Clarke, 2006).

To demonstrate dependability or the reliability of our coding (Lincoln & Guba, 1985), three research assistants (the last three authors) independently coded the same two interviews (6% of the data set). Following this initial round of systematically assigning codes to text units, the percentage of agreement across the three raters was 99% for convergence (Kappa = .99) and 94% for divergence (Kappa = .49). Coders then met to jointly discuss their results, calibrate their coding metrics, and update and refine the coding manual. Interviews were then coded independently (Schreier, 2012), but approximately two weeks later, one interview was coded by all three coders to check and ensure consistency. The additional interview that was coded together yielded a 99% agreement for convergence and divergence (Kappa =.99), indicating almost perfect agreement (McHugh, 2012). All disagreements were discussed until a consensus was reached.

**Interview Results**

*Reactions to the Knowledge Divergence/Convergence Question*

Six of the 32 interviewees highlighted the good and interesting nature of the question, and two commented that it was a hard question to answer. Nine PIs/co-PIs affirmed that a balance needs to be achieved between knowledge divergence and convergence. For example, two interviewees responded:

> "If we've got an unlimited amount of time, we would be able to learn everything. But given that that's not the case, I think there is a very specific and very important need of identifying what we really need to learn from the other field." (I16)

> "What should we make more divergent? Well, there's no point in…every researcher on both sides by the team learning everything there is to know to pass the prelims on the other discipline." (I15)

*Coding Themes*

Table 1 lists the second-order codes derived from the first-order codes and the overarching themes that united the second-order codes. Four broad themes emerged from the interviews: 1) values (cross-disciplinary respect, openness) 2) vision (research goals, outcomes) 3) research content (theory, hypotheses, methodology, and analyses), and 4) teamwork (roles, scheduling). Tables 2 and 3 summarize knowledge convergence and divergence results, respectively, including the number of interviewees mentioning each category, the number of times each category was mentioned in interviews (some interviewees discussed multiple aspects of a code), and illustrative quotes.

A broad comparison of Tables 2 and 3 reveals that interviewees were more likely to discuss knowledge convergence than divergence. Fifteen percent (15%) of respondents mentioned values and were unanimous in their agreement that cross-disciplinary respect and openness to new ideas should be shared by PI/co-PI teams, as evidenced by no responses coded as divergent for this first theme.

The second theme of vision was the most popular response, being mentioned as convergent by 39% of interviewees and in 54% of interviews, as several participants mentioned this theme multiple times in their answer. Similar to the response pattern for values, interviewees concurred that research goals should be shared (21%) and not held uniquely (0%). However, for research outcomes, interviewee comments were split across convergent (18%) and divergent (12%) categories. A close examination of remarks reveals that comments indicating convergence focused on the choice of which cross-disciplinary journal to publish in, what was cutting edge in the field, and the significance of the outcomes. In contrast, comments coded as divergent emphasized the need to contribute to one's own discipline due to tenure and promotion requirements. For example, social scientists should communicate to social science audiences and researchers from technical backgrounds should communicate to technical audiences because disciplinary outlets have different styles and values. As illustrated below, some interviewees' answers represented both convergent and divergent perspectives (and were therefore coded as both):

> "I think that there is one problem about what we're to publish. And…these…often feel a lot like ad hoc kind of decisions are made. And right now, for example, we've been lucky that we targeted a multidisciplinary journal that works for both of us…But each of us should say, 'Okay, well,…I need to have a publication in this disciplinary journal.' And [he] could say the same." (I22)

> "I think the publication is useful, but then getting that aligned, but I don't think it has to be 100% if I guess maybe, like 75% alignment. So, I think a challenge too, is that if you are in, say psychology or sociology, then you're not going to get much credit for publishing at CHI conference or Computer Science Conference or even a computer science journal, you're not going to get much credit for that." (I23)

For the third research theme of research content, both second-order codes (theory/hypotheses and methodology/analyses) were represented by comments coded as both convergent and divergent. Theory/hypotheses was an unpopular category. Only two participants (6%) stated that conceptual frameworks should be shared by the research team, and a single respondent (3%) said that they should remain unique to investigators. In contrast, while 9% of interviewees supported that methodology and analysis should be convergent, 27% supported divergence, which was the largest interviewee percentage across all second-order codes. As revealed by the illustrative quotes in Tables 2 and 3, the minority of participants coded as convergent discussed general methods for investigating the question and overarching approaches for how the data will be used and what variables were examined. However, interviewees coded as divergent discussed operational details and specific algorithms, software applications, and techniques (e.g., Qualtrics, coding, machine learning).

The fourth theme, teamwork, was mentioned by 9% of interviewees. Similar to disciplinary respect/openness and research goals, respondents were unanimous in their agreement that role assignments and scheduling should be shared by PI/co-PI teams, with no responses coded as divergent for this theme.

**Interview Discussion**

Given the paucity of research regarding how divergent and convergent knowledge should be integrated, we started with the recommended inductive approach (Edmondson & McManus, 2007). Coding interview data without a pre-existing theoretical framework (Braun & Clarke, 2006) yielded four primary themes: values, vision, research content, and teamwork.

What knowledge should be shared versus uniquely held by cross-disciplinary team members? Interviewees agreed that cross-disciplinary respect/openness, research goals, and teamwork should be shared in teams. In contrast, PIs/co-PIs concurred that operational details of methodologies could remain divergent. Split responses occurred for theory/hypotheses and research outcomes, with some interviewees commenting that these categories should be shared across team members while others indicated that they should remain uniquely held.

These findings are promising in two respects. First, what emerged was an initial framework of categories and sub-categories that cross-disciplinary researchers find relevant when considering convergent and divergent knowledge (see Table 1). Second, results revealed an initial consensus on what knowledge should be shared (cross-disciplinary respect, research goals, teamwork) and uniquely held (operational details of methodologies).

Despite the richness of qualitative data to enhance theory development, triangulating methodologies is commonly recommended to check the interpretation of the coded data and to overcome the weaknesses in any one method (e.g., Braun & Clarke, 2006; Gibson, 2017). Therefore, we adopted a sequential two-study design in which qualitative data are first collected and analyzed, followed by quantitative data (Srnka & Koeszegi, 2007). Specifically, building upon the interview results, we administered surveys to the same population of EAGER grant awardees. In contrast to a single interview question presenting knowledge convergence and divergence as a dichotomy, we assessed the extent to which PIs/co-PIs had a more unique or shared understanding of the coded themes via a 10-item questionnaire on a divergence-convergence continuum.

Extending the interview results, we also measured an affective outcome: perceived collaboration to unpack additional knowledge sharing patterns among cross-disciplinary researchers. The primary research question addressed by survey results was, “How does the extent to which cross-disciplinary team members report more of a unique or shared understanding of relevant team knowledge affect perceived collaboration (i.e., satisfaction with collaboration, the impact of collaboration, and trust and respect)?”

## SURVEYS

### Survey Recruitment and Sample

All 149 EAGER PIs and co-PIs in the sample were contacted via email and asked to complete a survey on cross-disciplinary team collaboration in their PI/co-PI EAGER team. Respondents were offered a $20 Amazon gift card for participation. Surveys were completed at the end of 2021 and the beginning of 2022.

The final sample included 38 unique responses, representing a response rate of 25.5%. Of the 38, 33 included complete survey data, and 5 were partially completed and unidentified, which did not allow us to link to interviews or archival data. A missing values analysis showed that responses were missing at random. Fourteen of the participants completing the survey also were interviewed (42% with 5 unidentified).

Independent samples t-tests were used to evaluate mean differences in the sample between the 33 identified PIs/co-PIs who completed the survey (N = 33) and those who did not (N = 116) for continuous variables available from archival data (team size, number of years since receiving the grant, award amount, number of universities represented in the grant, and number of years with a PhD). Consistent with the respondents who were interviewed, a marginal mean difference was found for the number of years since receiving the grant ($t = 1.93$, $p < .10$), which showed a mean difference of about 1 year (0.76 years). Respondents had an average of 5.65 years since receiving their grant (SD = 2.11), whereas non-respondents had an average of 6.41 years since receiving their grant (SD = 1.98). All other comparisons were non-significant.

Most respondents were White (60%), with 20% Asian/Pacific Islanders, 2.9% Black/African American, 2.9% from multiple races, and 14.3% selecting "other." Compared to the interview sample, survey respondents included more females (45.7%), with a majority of males (51.4%) and one non-binary participant (2.9%). The sample ranged in age from between 30-39 years and 70 or older, with most responses between 40-49 years (45.7%). The average number of years since interviewees received their Ph.D. (from 2022) was 20.52 (Median = 17, SD = 11.24), with a range of 6 to 53. Organizational tenure ranged from between 1-5 years to more than 20 years, with 11-15 years being the most frequently reported (23.5%).

The survey sample included 27 distinct EAGER projects (46.6% of the larger sample of 58 EAGER grants (5 interviewees did not report identifying information to link to archival data). Awards averaged $234,413 (Median = $234,251, SD = $ 74,776), ranging between $90,000 to $315,997. The average number of years since the EAGER grant was awarded (from 2022) was 5.65 years (SD = 2.11), with a range of 2.74 to 8.61 years. Six respondents overlapped with other respondents in representing the same EAGER grant.

Respondents represented an average PI/co-PI team size of 2.73 members (*SD* = 0.98), with a range of 2 to 5. The gender composition of the teams was mostly mixed (57.6%), with male-only and female-only comprising 30.3% and 12.1% of the sample, respectively. Nearly two-thirds (63.64%) of PI/co-PI teams were from the same university, with a maximum of three universities represented.

### Survey Measures

*Convergence and Divergence Scale*

For knowledge convergence and divergence items, participants were given the following prompt and instructions:

> "In multidisciplinary teams, members need to think differently to broaden expertise among members AND to think similarly to operate as a unified whole. That is, both unique and shared knowledge have been shown to improve team performance.
>
> Please indicate the extent to which PI/co-PIs had more of a unique understanding (different thinking) or more of a shared understanding (similar thinking) for each of the following components of your EAGER grant. If the component was not relevant to your EAGER grant, please select N/A."

Items were generated for this research based on the themes that emerged from the interview study, except for cross-disciplinary values, for which there is a pre-existing scale (see below). Specifically, we constructed 10 total items divided into vision (3 items assessing goals and outcomes), research content (4 items assessing theory, methodology (general approach and technical details), and analysis), and teamwork (3 items assessing how, who and when work should be accomplished) sub-scales. The following scale anchors were used: 1 = completely unique, 2 = somewhat unique, 3 = blank, 4 = somewhat shared 5 = completely shared.

A sample item for vision was "What we plan to accomplish (e.g., research mission, purpose, goals)." A sample item for research content included, "How we conduct the research (e.g., overall methodology, why we chose that approach)." A sample item for teamwork was, "Who does what (member roles and responsibilities and how they intersect to work as a team)." All scale items are shown in Tables 4 and 5.

**Actual and Ideal Knowledge Convergence.** Respondents were first asked to answer the extent of knowledge convergence for their *actual* EAGER grant work (the degree to which PI/co-PIs had a unique or shared understanding). Participants were then asked to complete the same 10 items with the following prompt: "With the benefit of hindsight, what level of unique versus shared understanding among PI/co-PI(s) WOULD HAVE BEEN IDEAL for your EAGER grant research?" Each knowledge convergence sub-scale yielded adequate internal consistency reliability for both actual EAGER grant work (Cronbach's alpha = .75 for vision, .85 for research content, and .85 for teamwork) and ideal EAGER grant work (Cronbach's alpha = .79 for vision, .88 for research content, and .93 for teamwork) items.

*Cross-Disciplinary Values*

Cross-disciplinary values were measured via the 10-item research orientation scale which assesses investigators' attitudes and values toward cross-disciplinarity (Hall et al., 2008). Three factors include unidisciplinarity (3 items), multidisciplinarity (2 items), and interdisciplinarity/transdisciplinarity (5 items, Hall, 2008). Unidisciplinarity represents working within a single field, and a sample item included, "The research questions I am often interested in generally do not warrant collaboration from other disciplines." In contrast, multidisciplinary collaborations involve researchers from different disciplines (e.g., "While working on a research project within my discipline, I sometimes feel it is important to seek the perspective of other disciplines when trying to answer particular parts of my research question").

Interdisciplinary/transdisciplinary collaborations demand a higher level of integration than multidisciplinary teams. Transdisciplinary collaborations require novel approaches that transcend individual disciplines (Hall et al., 2008). A sample item is, "Although I was trained in a particular discipline, I devote much of my time to understanding other disciplines in order to inform my research." All items were measured on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Demonstrating acceptable internal consistency reliability, Cronbach's alpha was .77, .76, and .80 for unidisciplinary, multidisciplinary, and interdisciplinary/transdisciplinary sub-scales, respectively.

*Perceived Collaboration*

Perceived collaboration was measured by adapting a scale developed by Masse and colleagues (2008), which consists of three correlated factors. The first 7-item factor assessed satisfaction with collaboration (acceptance of new ideas, communication, capitalizing on researcher strengths, organization, conflict resolution, working styles, and discipline involvement) on a 5-item scale ranging from inadequate to excellent. One item in the Masse and colleagues (2008) scale measuring the involvement of collaborators from outside the center was omitted because it did not apply to the EAGER sample. Cronbach's alpha was .97. The second 6-item factor measured the impact of collaboration (meeting productivity, product productivity, overall productivity, research productivity, quality research, and time burden). The first three items utilized a 5-item scale ranging from inadequate to excellent, while the second three items used a 5-item Likert scale ranging from strongly disagree to strongly agree. Cronbach's alpha was .85. The third 4-item factor measured trust and respect (comfort showing gaps in knowledge, trust, openness to criticism, respect) on a 5-item Likert scale (1=strongly disagree; 5=strongly agree). Cronbach's alpha was .93.

## Survey Results

### *Sample Comparison*

A one-way analysis of variance evaluated mean differences in the sample across four groups of participants: archival only (N = 97), interview only (N = 19), survey only (N = 19), and interview and survey (N = 14). Results showed significant mean differences in team size ($F(3, 145) = 5.04$, $p = .002$) across the four groups of participants. Post hoc comparisons using the Least Significant Difference (LSD) test revealed that respondents who only participated in the survey had a significantly higher team size ($M = 3.16$, $SD = 1.07$) than those who only completed the interview ($M = 2.47$, $SD = 0.61$) and those who completed both the survey and interview ($M = 2.14$, $SD = 0.36$). Similarly, archival-only respondents had a marginally higher team size ($M = 2.91$, $SD = 0.93$) than interview-only respondents ($M = 2.47$, $SD = 0.61$) and a significantly higher mean difference than survey and interview respondents ($M = 2.14$, $SD = 0.36$). No mean differences in team size were observed for archival-only and survey-only participants. All other comparisons were non-significant.

### *Actual and Ideal Knowledge Convergence*

**Descriptives and Frequencies.** Table 4 presents descriptives and frequencies for items reflecting whether a more unique or shared understanding was needed for PI/co-PI *actual* EAGER grant work. Across the vision, research content, and teamwork sub-scales, responses were skewed toward convergence (all items above 52%). Items with the top convergence ratings (above 63%) were in the vision ("what we accomplish," "what we produce") and teamwork ("how we accomplish tasks," "who does what") categories. Consistent with the interview data, where we publish" evidenced less convergence (52.78%) than the other two vision items. Interestingly, "when the work should be accomplished" was also rated as having lower sharedness (58.33%) than the other two teamwork items. All items with the least convergence fell in the research content sub-category, but the majority of respondents still rated theory, methodology, and analysis as being more similar than unique in their PI/co-PI teams (52.78-58.33%).

Parallel to Table 4, Table 5 depicts descriptives and frequencies for what pattern of divergence and convergence would have been *ideal* for PI/co-PI EAGER grant work. Responses were again skewed toward convergence (all items 50% or above). The highest convergence ratings were all three teamwork items (79.41-82.86%), followed by the first two vision items (what we plan to accomplish (75.76%) and what we produce (67.65%)). Similar to the actual EAGER grant work results, respondents rated "where we publish" as lower in agreement (52.94%) than the other two vision items. Again, the research content sub-category was rated as needing the least convergence (50.00-62.86%). Notably, only 50% rated that theory should be convergent within their PI/co-PI teams.

A paired comparison t-test comparing actual ($M$=3.55) versus ideal ($M$=3.75) EAGER grant overall convergence scales revealed a marginally significant difference ($t(33) = -1.94, p = .061$). Sub-scale analyses showed that the means for ideal ($M$=4.25) and actual ($M$=3.73) knowledge convergence differed significantly for the teamwork subscale ($t(33) = -2.96$, $p = .006$). Each of the items in the teamwork subscale were different across actual versus ideal responses. Therefore, participants reported that they should have had more similar thinking on work strategy, meeting structure, member roles and responsibilities, deadlines, and work pacing. No significant mean differences were found between actual versus ideal knowledge convergence for vision or research content sub-scales or items. Although not significantly different, it is worth noting that respondents reported higher means for ideal than actual convergence for all items except theory ($M$=3.45 for actual and $M$=3.24 for ideal) and the technical details of methods ($M$=3.35 for actual and $M$=3.32 for ideal).

**Correlations.** As shown in Table 6, overall scales for actual and ideal knowledge convergence were positively correlated ($r$ (32) = .66, $p$ <.001). The three actual convergence sub-scales were moderately correlated ($r$ (34) = .51-.66, $p$ <.001). Ideal convergence sub-scales yielded lower intercorrelations, with a non-significant association between research content and teamwork ($r$ (33) = .17, $p$ = .32). Vision correlated most highly with teamwork ($r$ (33) = .67, $p$ <.001), followed by research content ($r$ (33) = .39, $p$ = .022).

Perceived collaboration scales were so highly correlated as to indicate redundancy ($r$ (36) = .83-.90, $p$ = <.001), so satisfaction with collaboration, the impact of collaboration, and trust and respect were combined into one scale (Cronbach's alpha = .97). Overall actual knowledge convergence was strongly associated with higher perceived collaboration ($r$ (34) = .60, $p$ = <.001). Convergence sub-scale correlations yielded a more detailed picture, as research content was less positively associated with perceived collaboration ($r$ (34) = .37, $p$ = .027) than vision ($r$ (34) = .58, $p$ = <.001) or teamwork ($r$ (34) = .63, $p$ = <.001). Examining the four research content *items* provided even greater nuance, as general methodology ($r$ (34) = .38, $p$ = .024) and analyses ($r$ (34) = .39, $p$ = .019) were significantly and positively correlated with perceived collaboration, but specific methodology was only marginally significant ($r$ (34) = .30, $p$ = .075) and theory was non-significant ($r$ (34) = .15, $p$ = .372). As expected, no significant correlations emerged between perceived collaboration and the overall ideal knowledge convergence scale or sub-scales ($r$ (33) = .01-.23, $p$ > .05).

**Open-Ended Example.** In addition to the actual and ideal knowledge convergence scale items, participants were also asked: "Please describe an example of when it would have been helpful for PI-co-PI(s) to develop more of a shared understanding. Or describe an example of when it would have been helpful for PI/co-PI(s) to develop more of a unique understanding (different expertise was necessary with little need for convergence)."

Similar to the scale-based results, most respondents answered in terms of convergence (77.77%), with one interviewee admitting:

> "Most of my responses are the same. I think it's good to have somewhat similar thinking, to allow for more flexibility and resilience." (I25)

Two PI/co-PI answers reflected the need for more sharedness on research content (one on theory and one on analysis), while one response identified needing to be on the same page on teamwork (dividing up tasks and assigning roles for paper writing). Five of the nine respondents (55.55%) wrote about vision, four of which emphasized grant output. Helping to interpret the lower agreement for where to publish evidenced in the survey items, PI/co-PI responses reflected both convergence and divergence, including:

> "There is a bit of trouble (but very manageable) about which discipline's journals are the appropriate target. We managed it by specializing in writing different things out of the data." (I138)

> "We tended to focus on shared output with the same venues but separating out our perspectives/products could have also been useful." (I53)

*Cross-Disciplinary Values*

As shown in Table 6, the pattern of intercorrelations was as expected, with unidisciplinary research orientation negatively correlated with multidisciplinary ($r$ (36) = -.55, $p$ <.001) and interdisciplinary/transdisciplinary ($r$ (36) = -.61, $p$ <.001) orientation, and the latter two strongly positively correlated ($r$ (36) =.73, $p$ <.001).

Unidisciplinary research orientation was marginally and negatively correlated with overall actual convergence ($r$ (34) = -.32, $p$ = .057). Sub-scale analyses revealed negative correlations between unidisciplinary research orientation and convergence on research content ($r$ (34) = -.34, $p$ = .044), vision ($r$ (34) = -.303, $p$ = .073), and teamwork ($r$ (34) = -.15, $p$ =.40), but only research content reached statistical significance. Multidisciplinary and interdisciplinary/transdisciplinary research orientations were not significantly correlated with overall actual or ideal convergence scales or sub-scales.

Following a similar pattern as above, no significant correlations between perceived collaboration outcomes emerged for multidisciplinary ($r$ (36) = .12, $p$ = .464) or interdisciplinary/transdisciplinary research orientations ($r$ (36) = .21, $p$ = .208). However, higher unidisciplinary orientation was associated with lower perceived collaboration ($r$ (36) = -.38, $p$ = .020).

### Survey Discussion

Three major results emerged from survey data. First, when PI/co-PIs were surveyed regarding what aspects of their research collaboration were (actual) and should have been (ideal) shared versus unique, both scale-based and open-ended responses favored knowledge convergence within teams rather than divergence. Second, respondents especially favored knowledge similarity over uniqueness for what they planned to accomplish, what they produced, how tasks would be completed, who did what, and when work should be done. However, where PI/co-PIs published and research content (theory, methodology, analysis) evidenced less knowledge convergence than other vision or teamwork items. These patterns were similar across actual and ideal knowledge convergence scales, but respondents reported that they wished they had more similar views on teamwork (how, who, and when work should be accomplished) than they actually did. Regarding values, higher unidisciplinary orientation was associated with lower convergence on research content (and vision was marginally significant).

Third, higher overall actual knowledge convergence was associated with higher perceived collaboration outcomes (satisfaction with collaboration, the impact of collaboration, and trust and respect). Vision and teamwork had higher positive correlations with perceived collaboration than research content. Of the research content items, only general methodology and analyses were significantly associated with perceived collaboration. Concerning values, PI/co-PIs with a greater unidisciplinary orientation reported decreased perceived collaboration.

### Survey Limitations

Despite multiple efforts to increase the sample size, only 38 PIs and co-PIs completed the survey, making this research more qualitative in nature than quantitative. The low sample size resulted in limited statistical power, which likely contributed to the marginal significance of several results. The small sample also did not permit reliable exploratory factor analyses to be performed on the 10-item actual or ideal convergence scales, which needs validation. In addition, because of the single survey administration, significant correlations could be due to common method bias (Podsakoff et al., 2003).

## ARCHIVAL RESEARCH

### Archival Methodology

*Procedure*

Using publicly available information (e.g., grants.gov, PI/co-PI vitas on university websites, LinkedIn), our research team collected and cataloged PI and co-PI research productivity during and after their EAGER award. We operationalized team research productivity as the total of publicly available conference papers, publications, and grants PIs and co-PIs produced with each other during and after their EAGER grant through the end of 2021. We counted conference papers, publications, and grants in which all PIs and co-PIs in a team were authors and in which only a partial subset were authors. For example, a team of four representing the disciplines of information science, computer science, math, and psychology wrote a three-person authored conference proceeding (information science, math, and computer science) as well as a two-person authored journal article (information science and psychology).

Because it is customary for grant awardees to request at least one or more no-cost extensions, it was impossible to precisely assess from publicly available data whether research productivity continued after their EAGER grant was completed. Therefore, research productivity produced after the EAGER award was received includes during the grant period and afterward.

*Sample*

Our sample included 31 PI/co-PI EAGER awardees who completed the survey (with identifying information) and produced archivally measured conference papers, publications and/or grants. Five of the 38 survey responses were partially completed and unidentified, which did not allow us to link them to archival data.

**Archival Results**

As shown in Table 6, the association between overall actual convergence and total PI/co-PI combined research team productivity (grants, publications, and conference presentations) during and after the EAGER award trended positive but was not significant ($r$ (31) = .22, $p$ = .240). The correlations between combined research team productivity and actual convergence sub-scales yielded similar results for vision ($r$ (31) = .29, $p$ = .111) and teamwork ($r$ (31) = .22, $p$ = .246), but a weaker relationship for research content ($r$ (31) = .08, $p$ = .663). No significant correlations emerged when we examined the association between overall actual convergence and conference presentations ($r$ (31) = .11, $p$ = .547), publications ($r$ (31) = .18, $p$ = .333), and grants ($r$ (31) = .03, $p$ = .862) separately.

Regarding values, a marginally significant relationship resulted between combined research team productivity and multidisciplinary research orientation ($r$ (33) = .33, $p$ = .059), with non-significant correlations found for interdisciplinary/transdisciplinary ($r$ (33) = .22, $p$ = .230) and unidisciplinary ($r$ (33) = -.11, $p$ = .545) research orientations. Table 6 includes the full correlation matrix.

**Archival Discussion**

How does the extent to which cross-disciplinary team members report more of a unique or shared understanding of relevant team knowledge affect archival measures of research productivity? Results revealed that higher convergence on vision, research content, and teamwork trended in the direction of more grants, publications, and conference presentations, but relationships were not statistically significant. A sub-scale analysis of actual convergence discovered that relationships with overall team productivity were higher in magnitude for vision and teamwork than research content, although none reached significance.

Regarding values, a multidisciplinary research orientation trended in the direction of more team conference presentations, publications, and grants, with interdisciplinary/transdisciplinary and unidisciplinary research orientations evidencing weaker relationships. Unidisciplinary, multidisciplinary, and interdisciplinary/transdisciplinary orientations exist on a continuum of increasing cross-disciplinary integration (Stokols et al., 2008). The multidisciplinary mindset may have yielded productivity outcomes more efficiently than the extensive collaboration interdisciplinary/transdisciplinary orientation would require. Since the EAGER grant was just one project of many that PI/co-PIs were involved with, interviewees often alluded to the limited time and resources they had for collaboration. Given these constraints, a multidisciplinary orientation may have yielded productivity outcomes more efficiently than the more extensive collaboration of inter/transdisciplinary research. More research is needed to test this post hoc speculation and to unpack why self-identified multidisciplinary researchers would yield higher magnitude correlations with research team productivity.

**Archival Limitations**

Perceptions of knowledge convergence may have been collected after research productivity, depending on where PIs/co-PIs were in their research and grant cycles. In addition, correlations do not imply causality. Thus, results cannot speak to whether the extent of knowledge uniqueness or sharing predicted the number of grants, publications, and conference presentations or vice versa.

Because of the low sample size, correlations needed to be higher to reach statistical significance. Therefore, results may be conservative and meaningful despite not being statistically significant. However, relationships should be tested with larger samples of cross-disciplinary researchers.

## OVERALL DISCUSSION

Results revealed a consistent pattern across interview, survey, and archival methodologies. Three major findings resulted from our mixed-methods research. First, interviews revealed an initial framework of knowledge categories relevant to cross-disciplinary researchers: 1) values (cross-disciplinary respect, openness) 2) vision (research goals, outcomes) 3) research content (theory, hypotheses, methodology, and analyses), and 4) teamwork (roles, scheduling). In a comprehensive review of the team cognition literature, these four themes are represented in a broader list of cognitive content, which is reflected in the question

"What is shared?" (see Table 6 in Mohammed et al., 2021). Complementing the deductive approach of past research, our study inductively derived these categories from cross-disciplinary PIs/co-PIs.

Second, both interview and survey results were skewed toward knowledge convergence rather than divergence. Comparably, more constructs in the team cognition literature emphasize cognitive similarity over diversity (Mohammed et al., 2021), and teams have been found to attend more to shared instead of uniquely held information (Sohrab, Waller, & Kaplan, 2015). Participants especially favored knowledge similarity over uniqueness for what they planned to accomplish, what they produced, how tasks would be completed, who did what, and when work should be done. Compared to vision and teamwork, less preference for convergence emerged for research outcomes (where to publish) and research content (theory, operational details of methodology, analysis).

Third, higher actual knowledge convergence (especially for vision and teamwork) was associated with higher perceived collaboration (satisfaction, trust, respect, research impact). Although not reaching statistical significance, higher sharedness on vision, teamwork, and research content (lower magnitude correlation) trended in the direction of higher research productivity (more grants, publications, and conference presentations). In contrast, unidisciplinary orientation was negatively correlated with higher perceived collaboration.

Below, we discuss the theoretical and practical implications, limitations, and future directions of our study.

**Theoretical Implications**

Communicating the wrong information in the wrong way with the wrong people at the wrong time has been blamed on a variety of high-profile team disasters and accidents (e.g., Bearman, Paletz, Orasanu, & Thomas, 2010, Bell & Kozlowski, 2011, Santos et al., 2013). In contrast, effectively leveraging knowledge is one of the hallmarks of successful cross-disciplinary teams (Paletz & Schunn, 2010; Salazar et al., 2012), as well as teams in general (e.g., DeChurch & Mesmer-Magnus, 2009; Faraj & Sproull, 2000; Mohammed et al., 2010). Meta-analytic research has established that knowledge divergence (e.g., different expertise) and knowledge convergence (e.g., shared understanding) independently and uniquely predict team processes and performance (e.g., DeChurch & Mesmer-Magnus, 2010; Niler et al., 2020). Researchers also concur that neither complete knowledge convergence nor complete divergence in teams is generally desirable (e.g., Klimoski & Mohammed, 1994). Too much convergence fails to harness member differences, while too much divergence fails to build enough consensus for the team to operate as a unified collective (Mohammed, 2001).

What we don't know, however, is how teams manage the tension between the necessary but opposing forces of knowledge convergence and divergence. This issue is critical to address because knowledge integration across disciplinary boundaries is time consuming, complex, and requires substantial member communication and interaction to develop (e.g., Grand et al., 2016; Salazar et al., 2012). Given the high level of specialization of disciplinary knowledge, communication exchanges can burden team members and contribute to communication overload (Larson et al., 2022). Therefore, building knowledge convergence when divergence is optimal squanders valuable team resources and may undermine the unique strengths that members bring to the team (Crawford & LePine, 2013). Although both the team cognition and cross-disciplinary team literatures have tended to emphasize knowledge convergence over divergence (e.g., Ávila-Robinson & Sengoku, 2017; Mohammed et al., 2021), more cross-disciplinary integration may not always be better (Larson et al., 2022). Indeed, the benefits of communication may be more curvilinear rather than linear (Crawford & LePine, 2013) and therefore only beneficial to teamwork up to a certain point. Unfortunately, however, extant research provides little direction in determining how knowledge divergence and convergence should exist in equilibrium.

Integrating the team cognition and cross-disciplinary team literatures, we begin to answer what knowledge should be shared and what knowledge should remain unique to individual members for cross-disciplinary teams to be effective. Results supported agreement among team members around the broader categories of vision and teamwork, while allowing for less consensus around the specifics of research content. Thus, convergence around what should be accomplished and produced as well as who should do what and when provided the shared understanding needed to move toward action, regardless of differing views on theories, hypotheses, methods, and analyses. In this way, unity and diversity coexist in the cross-disciplinary teams' knowledge architecture.

Similar to the cross-disciplinary and team cognition literatures, interviewees and survey respondents favored knowledge convergence over divergence. Furthermore, knowledge convergence positively predicted desirable affective outcomes and trended in the direction of higher research productivity. As expected, having more of a unidisciplinary orientation was associated with lower perceived collaboration.

## Practical Implications

How can team leaders help to set cross-disciplinary teams up for success? Our results suggest that cross-disciplinary researchers should arrive at consensus on two basic categories of questions: 1) What will we accomplish and produce? and 2) Who will do what and when to accomplish the work? Notably, the latter category of teamwork was the only one in which PI/co-PIs in our sample rated as needing significantly greater convergence than what actually occurred in their teams. Therefore, team members should pay particular attention to getting on the same page about roles, responsibilities, and scheduling.

Compared to vision and teamwork, findings indicated that less convergence was needed for research outcomes (where to publish) and research content (theory, operational details of methodology, analysis). Teams should explicitly discuss the extent to which a unique versus shared understanding is needed in these areas, commensurate with the goals and stages of their research.

Given that higher unidisciplinary orientation was associated with lower perceived collaboration in our study, teams may want to assess research orientation and collaboration readiness (Hall et al., 2008) prior to inviting members to join cross-disciplinary teams. Due to the qualitative and preliminary nature of our findings, we strongly advise further research replicating our findings with a larger sample representing a broader range of cross-disciplinary teams before implementing findings.

## Limitations and Future Directions

Several limitations must be acknowledged. First, although combining interview, survey, and archival data made deeper and more novel interpretations possible (Gibson, 2017), we believe the qualitative aspects of this paper provide the most significant contribution due to the low sample size of the survey. Future research should significantly expand survey data collection to determine the factor structure of the actual and ideal knowledge convergence scale and its convergent, discriminant, and predictive validity.

Second, the results of this study should be interpreted in relation to the limited sample size, which was limited to PI/co-PIs awarded EAGER grants studying cybersecurity. For example, our finding that theory failed to emerge as a popular category in interviews and only 50% rated that theory should be convergent in PI/co-PI teams may not generalize to other cross-disciplinary topics. Therefore, studies featuring a greater range of cross-disciplinary research and contexts should be conducted.

Third, participants were asked to reflect on their team collaboration between 2 and 8 years since their EAGER grant had been awarded. Thus, both interview and survey responses may have been limited by retrospective bias (Evans & Leighton, 1995). However, beyond mere perceptual data, archival analyses assessed non-self-report research productivity. Given the time needed to vet research output via peer review, the 2–8-year time lag allowed for a more precise assessment of the number of conference presentations, publications, and grants.

Nevertheless, a fourth weakness in our research is that our archival analyses underestimated the research productivity of later rather than earlier grant awardees. Because we ended archival analyses at the end of 2021, 2019 EAGER grant awardees only had two years of productivity included in their output score versus eight years of productivity for 2013 awardees. In addition, the research output of PI/co-PIs may have been adversely impacted by the COVID-19 pandemic in 2020 and 2021.

Fifth, some of the consistency between survey and interview results was due to the 42% overlap in respondents who completed both methods. Future research should therefore replicate these results in additional cross-disciplinary samples.

Sixth, we mainly interviewed and surveyed only one member per team, and only PIs or co-PIs. Rather than relying on a single viewpoint to represent the team, future quantitative studies should consider measuring knowledge convergence as a shared group property. Admittedly, a team-based approach is more labor-intensive. This is because it requires asking all team members to complete the survey (e.g., graduate students, postdocs, undergraduates, research staff), checking responses for agreement among members, and aggregating scales by mean. However, this approach may result in a more comprehensive, team-level assessment of the knowledge that was shared versus what remained unique in the team.

The optimal level of knowledge convergence in cross-disciplinary teams that contributes to effective processes and outcomes will depend upon several factors, including the level of interdependence among members, the goals of the research, and what stage of research the team is in. For example, if the research is intended to be more transdisciplinary (extending discipline-specific theories so new approaches are created) than multidisciplinary (working from own discipline-specific perspectives) (Bammer et al., 2020; Klein, 2010), more knowledge convergence on research content is likely needed. More knowledge divergence early in the team's life cycle may be helpful to maximize the number of viewpoints and ensure a comprehensive treatment of issues (e.g., Walsh et al., 1988; Wang et al., 2019). In contrast, more knowledge convergence may be beneficial as teams move toward implementation (e.g., Kilduff et al., 2000). The extent to which members have worked with each other in the past as well as the level of geographic dispersion and trust between team members are also potential moderators. Therefore, future research should investigate moderators of the knowledge convergence - team outcome relationship to assess the conditions under which increased sharedness improves or hinders perceived collaboration and research productivity.

## CONCLUSION

Although the need for both knowledge convergence and divergence in teams is recognized in the literature, how teams effectively manage the tension between the two remains unclear. To investigate this, our research utilized a mixed-method approach with grant funded teams comprising different disciplines. Results indicated a preference for knowledge convergence in team vision and teamwork, while research outcomes and content showed less preference for convergence. Higher levels of knowledge convergence were associated with greater collaboration satisfaction, trust, respect, and research impact as well as trended in the direction of increased research productivity. These results have significant implications for understanding and improving cross-disciplinary team dynamics and outcomes.

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## APPENDIX

**TABLE 1**
**ORGANIZATION OF THEMES, SECOND-ORDER CODES, AND FIRST-ORDER CODES**

| Second-Order Codes | First-Order Codes |
|---|---|
| **Theme 1: Values** | |
| • **Disciplinary respect & openness** | Understanding the history and background of others' disciplines, respect for others' disciplines, openness to new ideas, not allowing egos to interfere with learning |
| **Theme 2: Vision** | |
| • **Research goals** | Purpose/rough plan, expectations about what want to get out of the collaboration, extent of cross-disciplinary collaboration desired |
| • **Research outcomes** | Where to publish, the best audience for papers, what is cutting edge and innovative in your field, what counts for tenure and promotion, communicating findings within disciplinary and cross-disciplinary journals |
| **Theme 3: Research Content** | |
| • **Theory & hypotheses** | Conceptual frameworks in the field, hypotheses |
| • **Methodology & analyses** | Method for investigating the question, what variables you will be examining, specific algorithms and methodologies (e.g., Qualtrics, coding, machine learning), operational details, technical details, software applications |
| **Theme 4: Teamwork** | |
| • **Role assignments & scheduling** | Who needs to do what, who will take the lead on what, timelines and schedules, what communication tools to use |

**TABLE 2**
**KNOWLEDGE CONVERGENCE RESULTS**

| What Knowledge Should be Shared? | | | |
|---|---|---|---|
| **Second-Order Codes** | **Number of Interviewees Mentioning Category & Percentage** | **Number of Times Mentioned in Interviews & Percentage** | **Illustrative Quotes** |
| **Theme 1: Values** | **5 (15.2%)** | **5 (15.2%)** | |
| • **Disciplinary respect & openness** | 5 (15.2%) | 5 (15.2%) | "Someone may say, 'Well, we have nothing to gain from that discipline.' If that person is very influential, then that will cause two disciplines to get away from each other in a very unproductive way." (I21)<br><br>"And sort of an openness to ideas that maybe you haven't encountered…, that nobody comes at it thinking they have all the answers already set up." (I26) |
| **Theme 2: Vision** | **13 (39.4%)** | **18 (54.5%)** | |
| • **Research goals** | 7 (21.2%) | 9 (27.3%) | "I would say that the key for us has been to continually revisit what we're doing, why we're doing it. Make sure we're not either of us going down rabbit holes." (I4)<br><br>"Getting a clear shared vision as to what the research should be about….where…one discipline is not in service to another one, I think that's going to be the hardest part. And that one, I think, is nonnegotiable, that it pretty much has to…be aligned. Because if it's not, then it's just going to be really messy." (I23) |
| • **Research outcomes** | 6 (18.2%) | 9 (27.3%) | "This is where things have to have to converge…we have to understand the meaning and the significance of those outcomes, how we get to those outcomes." (I1)<br><br>"So, what do they want to get out of it? And I think understanding the other person's incentives…is also pretty important. So again, ours were naturally aligned. But for computer scientists, do they just want to build something or what kinds of research would be of interest to them? That |

| | | | |
|---|---|---|---|
| | | | requires lots and lots of conversations to understand the culture with different discipline, which is not going to be easy." (I23) |
| **Theme 3: Research Content** | **5 (15.2%)** | **5 (15.2%)** | |
| • **Theory & hypotheses** | 2 (6.1%) | 2 (6.1%) | "I think that would have been really great if we stuck with that longer, and really looked at the different theories and approaches in the field and used each other's fields to kind of critically evaluate what's going on. So I would say, even though [we] weren't successful, I do think…in general, to be able to use similar theoretical approaches I think could be valuable." (I6)<br>"Hypotheses … those kinds of decisions…the PIs would take in the presence of each other." (I7) |
| • **Methodology & analyses** | 3 (9.1%) | 3 (9.1%) | "I know a fair amount of what she does in terms of interface design, and she knows a fair amount of what I do. I think there was not that much division. There was a much more active involvement… even in some of the operational stuff, we would just routinely run everything by each other." (I7)<br>"If we do not agree on a method for investigating the question, then usually what happens is that we move on to a different question." (I11) |
| **Theme 4: Teamwork** | **3 (9.1%)** | **4 (12.1%)** | |
| • **Role assignments & scheduling** | 3 (9.1%) | 4 (12.1%) | "Decisions about how to write this up, how to divvy up the project into different papers, who's going to take a lead on what, what would be kind of our best audience for this, those kinds of decisions we would pretty much take, the PI's would take in the presence of each other." (I7)<br>"I suppose also, there's the practical, like, how do we communicate? Or are you guys comfortable with using this tool versus the other (e.g., LaTeX)? And so that helped a lot." (I22) |

**TABLE 3**
**KNOWLEDGE DIVERGENCE RESULTS**

| What Knowledge Should be Uniquely Held? | | | |
|---|---|---|---|
| **Second-Order Codes** | **Number of Interviewees Mentioning Category & Percentage** | **Number of Times Mentioned in Interviews & Percentage** | **Illustrative Quotes** |
| ~~**Theme 1: Values**~~ | **0** | **0** | |
| • **Disciplinary respect & openness** | 0 | 0 | |
| ~~**Theme 2: Vision**~~ | **4 (12.1%)** | **4 (12.1%)** | |
| • **Research goals** | 0 | 0 | |
| • **Research outcomes** | 4 (12.1%) | 4 (12.1%) | "I think what needs to be divergent is who is benefiting from our work together. And how can we communicate that in a way that is accessible to people? So we had a submission just accepted at [a social science journal] for our work…And so, you know, the way that we're going to communicate that to [psychology] participants is going to be very different from how we're going to communicate our findings to computer scientists. So I think it's critical that in multidisciplinary teams, the different disciplines communicate in a way that makes their products useful for the most people within their fields." (I6)<br><br>"I assume that in a certain sense, there is a little bit of data…that each party would also want to keep…a little bit separate to…get the, I don't know, the recognition, the credit from it…because ultimately, like we are still judged in the departments and departments are still largely disciplinary entities. And so you need to…bring something back home essentially." (I22) |

| | | | |
|---|---|---|---|
| **Theme 3: Research Content** | **10 (30.3%)** | **12 (36.4%)** | |
| • **Theory & hypotheses** | 1 (3.0%) | 1 (3.0%) | "So I think the things that should remain different are basically theories and the background or settings in which you place your research." (I11) |
| • **Methodology and analyses** | 9 (27.3%) | 11 (33.3%) | "I think it's perfectly fine to have different methodologies that you value in your discipline. They have long histories and the way an HCI designer or the way a computer scientist sort of approaches a piece of research is going to be different methodologically from what we [social scientists] do…so I would say methodologies I think are okay to keep their distinction." (I4)<br><br>"I'm not sure that you have to be committed to the same methods, because you're coming from different disciplines, but certainly have a common problem that you're solving." (I28) |
| **Theme 4: Teamwork** | **0** | **0** | |
| • **Role assignments & scheduling** | 0 | 0 | |

**TABLE 4**
**KNOWLEDGE CONVERGENCE ITEM DESCRIPTIVES AND FREQUENCIES FOR PI/CO-PI ACTUAL EAGER GRANT WORK**

| | Means (SDs) | Frequencies | | | |
|---|---|---|---|---|---|
| | | Completely and Somewhat Unique between PIs/co-PIs 1 & 2 | 3 | Completely and somewhat Shared between PIs/co-PIs 4 & 5 | N |
| **Vision** | | | | | |
| What we plan to accomplish (e.g., research mission, purpose, goals) | 3.72 (.94) | 13.89% | 19.44% | 66.67% | 36 |
| What we produce (e.g., publications, conference presentations, patents, prototypes) | 3.72 (1.00) | 16.67% | 16.67% | 66.67% | 36 |
| Where we publish and/or present results (e.g., specific journal outlets, conferences, etc.) | 3.50 (1.16) | 27.78% | 19.44% | 52.78% | 36 |
| **Vision Average Percentages Across Items** | | 19.44% | 18.52% | 62.04% | |
| **Research Content** | | | | | |
| Our theoretical framework or model (what theories will we draw from) | 3.44 (1.13) | 25.00% | 22.22% | 52.78% | 36 |
| How we conduct the research (e.g., overall methodology, why we chose that approach) | 3.39 (1.23) | 30.56% | 13.89% | 55.56% | 36 |
| How we conduct the research specifically (e.g., detailed technical aspects of methods) | 3.44 (1.23) | 25.00% | 16.67% | 58.33% | 36 |
| How we analyze the data | 3.33 (1.15) | 27.78% | 19.44% | 52.78% | 36 |
| **Research Content Average Percentages Across Items** | | 24.31% | 17.36% | 58.33% | |
| **Teamwork** | | | | | |
| How we accomplish research tasks as a team (e.g., work strategy, meeting structure, plans and activities for work execution) | 3.72 (1.00) | 16.67% | 16.67% | 66.67% | 36 |
| Who does what (member roles and responsibilities and how they intersect to work as a team) | 3.89 (1.12) | 11.11% | 25.00% | 63.89% | 36 |
| When the work should be accomplished (e.g., deadlines, pacing of work, sequencing of what should happen first, second, third, etc.) | 3.75 (1.11) | 16.67% | 25.00% | 58.33% | 36 |
| **Research Process Average Percentages Across Items** | | 14.81% | 22.22% | 62.96% | |

NOTE. N= sample size. SD = standard deviation. Response scale: 1 = completely unique 2 = somewhat unique 3 = blank 4 = somewhat shared 5 = completely shared.

**TABLE 5**
**KNOWLEDGE CONVERGENCE ITEM DESCRIPTIVES AND FREQUENCIES FOR PI/CO-PI IDEAL EAGER GRANT WORK**

| | **Means (SDs)** | **Frequencies** | | | |
|---|---|---|---|---|---|
| | | Completely and Somewhat Unique between PIs/co-PIs **1 & 2** | **3** | Completely and Somewhat Shared Between PIs/co-PIs **4 & 5** | **N** |
| | **Vision** | | | | |
| What we plan to accomplish (e.g., research mission, purpose, goals) | 3.91 (1.01) | 15.15% | 9.09% | 75.76% | 33 |
| What we produce (e.g., publications, conference presentations, patents, prototypes) | 3.79 (1.07) | 17.65% | 14.71% | 67.65% | 34 |
| Where we publish and/or present results (e.g., specific journal outlets, conferences, etc.) | 3.68 (1.01) | 11.76% | 35.29% | 52.94% | 34 |
| **Vision Average Percentages Across Items** | | 14.85% | 19.70% | 65.45% | |
| | **Research Content** | | | | |
| Our theoretical framework or model (what theories will we draw from) | 3.24 (1.08) | 32.35% | 17.65% | 50.00% | 34 |
| How we conduct the research (e.g., overall methodology, why we chose that approach) | 3.51 (1.15) | 22.86% | 14.29% | 62.86% | 35 |
| How we conduct the research specifically (e.g., detailed technical aspects of methods) | 3.31 (1.08) | 25.71% | 20.00% | 54.29% | 35 |
| How we analyze the data | 3.51 (1.12) | 25.71% | 11.43% | 62.86% | 35 |
| **Research Content Average Percentages Across Items** | | 24.64% | 16.66% | 58.70% | |
| | **Teamwork** | | | | |
| How we accomplish research tasks as a team (e.g., work strategy, meeting structure, plans and activities for work execution) | 4.51 (0.82) | 2.94% | 17.65% | 79.41% | 34 |
| Who does what (member roles and responsibilities and how they intersect to work as a team) | 4.26 (0.98) | 8.57% | 11.43% | 80.00% | 35 |
| When the work should be accomplished (e.g., deadlines, pacing of work, sequencing of what should happen first, second, third, etc.) | 4.29 (0.96) | 8.57% | 8.57% | 82.86% | 35 |
| **Research Process Average Percentages Across Items** | | 6.69% | 12.55% | 80.76% | |

NOTE. N= sample size. SD = standard deviation. Response scale: 1 = completely unique 2 = somewhat unique 3 = blank 4 = somewhat shared 5 = completely shared.

**TABLE 6**
**MEANS, STANDARD DEVIATIONS AND CORRELATIONS AMONG ALL GROUP-LEVEL VARIABLES**

| Variable | *M* | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Actual convergence (values) | 3.65 | .85 | | | | | | | | | | | | | |
| 2. Actual convergence (research context) | 3.40 | .98 | .52** | | | | | | | | | | | | |
| 3. Actual convergence (teamwork) | 3.79 | .94 | .66** | .51** | | | | | | | | | | | |
| 4. Actual convergence (overall) | 3.69 | .78 | .83** | .86** | .83** | | | | | | | | | | |
| 5. Ideal convergence (values) | 3.74 | .91 | .49** | .43* | .26 | .47** | | | | | | | | | |
| 6. Ideal convergence (research context) | 3.40 | .94 | .28 | .74** | .38* | .61** | .39* | | | | | | | | |
| 7. Ideal convergence (teamwork) | 4.24 | .87 | .31 | .33 | .36* | .40* | .67** | .17 | | | | | | | |
| 8. Ideal convergence (overall) | 3.76 | .69 | .46** | .68** | .44** | .66** | .84** | .75** | .72** | | | | | | |
| 9. Unidisciplinary research orientation | 2.31 | .90 | -.30 | -.34* | -.15 | -.32 | -.12 | -.15 | -.17 | -.19 | | | | | |
| 10. Multidisciplinary research orientation | 3.75 | 1.00 | .02 | .21 | .08 | .14 | -.02. | .19 | .10 | .13 | -.55** | | | | |
| 11. Interdisciplinary research orientation | 3.81 | .84 | -.09 | .18 | -.02 | .05 | -.19 | .20 | -.08 | .01 | -.61** | .73** | | | |
| 12. Perceived collaboration | 4.24 | .77 | .58** | .37* | .63** | .60** | .01 | .23 | .14 | .18 | -.38* | .12 | .21 | | |
| 13. Research productivity (archival) | 5.62 | 7.20 | .29 | .08 | .22 | .22 | -.12 | .10 | .03 | .02 | -.11 | .33 | .24 | .22 | |

*Note*: N=30
**p<.01; *p<.05; +p<.10